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13. ABSTRACT (Maximum 200 words)

A three year ARO project has resulted in important novel non-linear image processing techniques that aim to facilitate target detection and tracking from video sequences involving severe clutter and change of target scale. One of the non-linear techniques developed is the morphological locally monotonic (LOMO) filter. Morphological LOMO filter is scalable to target sizes and eases scale sensitive target detection. Another significant development is the speckle reducing anisotropic diffusion (SRAD) method for eradicating clutter and noise from radar and ultrasound imagery. A third development is a generic connected filtering technique called the inclusion filter, which has been shown to improve tracking in clutter. Target shape and size as well as other set theoretic criteria can be constrained using the inclusion filter, without distorting target edges. Yet another significant advancement in target tracking has been made through developing projection model active contour models and related Monte Carlo methods. The projection model tracking methods have been shown to be resilient to severe clutter and change of target scales. The ARO project has supported 10 graduate students and 3 undergraduate students in the process of earning engineering degrees from University of Virginia. The project has also led to over 25 peer reviewed publications.

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A. STATEMENT OF THE PROBLEM STUDIED

The primary goal of a missile-based imaging system is to detect and recognize a particular target and then to track the target as the missile advances. Current automatic target recognition (ATR) and tracking algorithms are sensitive to background clutter and scale changes. Missile-based acquisition and tracking systems encounter a rapidly changing background and extreme scale changes as the missile approaches the target. When imaging in these adverse conditions, even simple detection and tracking tasks become increasingly difficult. To counteract the susceptibility of the image processing systems to clutter and scale changes, robust image processing techniques must be developed. These methods must reliably extract the target information from degraded, cluttered imagery.

In this project, we address two problems that have plagued recent Army ATR and tracking systems: **clutter** and **scale**. In discussions with the ATR and tracking groups at the U.S. Army Space and Missile Defense Command, the problems of clutter and scale have been identified as high priority research challenges in the image processing area. Responding to this challenge, we have developed novel nonlinear processing methods that reduce the effect of clutter and can operate at a variety of feature scales.

Several non-linear image processing methods have been developed with the support of this Army Research Office grant. We developed the morphological (locally monotonic) LOMO filter, which is easily adapted to the scale of the target and is able to remove sub scales image features while retaining target features of interest that are above certain scale (*e.g.*, size). The implementation of the morphological LOMO filter is simple and computationally attractive. Another significant non-linear filter developed in our research effort is the speckle reducing anisotropic diffusion (SRAD) for radar and ultrasound imagery. Very encouraging enhancement results have been obtained through SRAD. We have also extended the two dimensional SRAD to three dimensions for image sequences. Among other significant non-linear image processing techniques is the development of a morphological connected operator the behavior of which is invariant under gray-scale inversion. Flexible filtering criteria including shape or size of the targets can be easily incorporated in this type of connected operators. We have also extended these connected operators to color and multispectral imagery.

Lastly, we describe new active contour methods for target tracking. The methods rely on projection models that maintain target shape while tracking. The novel motion gradient vector flow algorithm is used to improve the tracking performance and to reduce the dependency on initial contour placement. In addition, target detection and tracking is enhanced by way of the gradient inverse coefficient of variation (GICOV) measure.

B. SUMMARY OF THE MOST IMPORTANT RESULTS

Locally Monotonic Filters and Non-linear Scalable Filters

The locally monotonic (LOMO) filters output a signal that is either increasing or decreasing within a local window of certain size (scale) (Bosworth and Acton, 2003). Figure 1 shows a 1D signal and LOMO outputs for increasing scales. We developed a theoretical connection between LOMO filters and mathematical morphology by creating LOMO filters using a combination of morphological operations (Bosworth and Acton, 2003). Morphological LOMO filter is advantageous since it is easily scalable, *i.e.*, it can eradicate noise and detail, and retain image features of desired size (scale). The filter can be effectively utilized in detecting targets of desired scales. Let *I* be an image intensity function and *B* be a symmetric flat morphological structuring element, then the morphological LOMO filter is defined via iterative implementation of

$$I \leftarrow \frac{1}{2}(I \circ B + I \bullet B), \tag{1}$$

where $\circ$ and $\bullet$ respectively denote morphological open and close operation (Bosworth and Acton, 2003). Figure 2 shows morphological LOMO filter on an image with increasing radius of structuring elements. We observe that details are removed as scale (radius of the structuring element) increases.
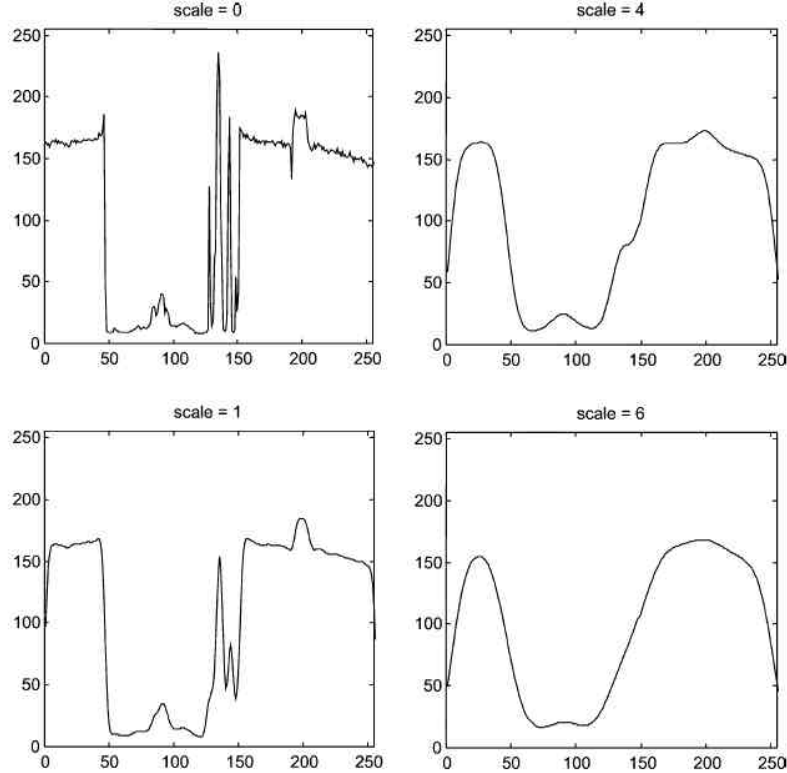

Figure 1 LOMO signals at increasing scales.

We have investigated the use of the LOMO filter for enhancement in automated target recognition and tracking, segmentation, and object-based image coding (Bosworth and Acton, 2000). For tracking in clutter, the LOMO filter has the advantages of low computational expense and direct specification of the target scale.
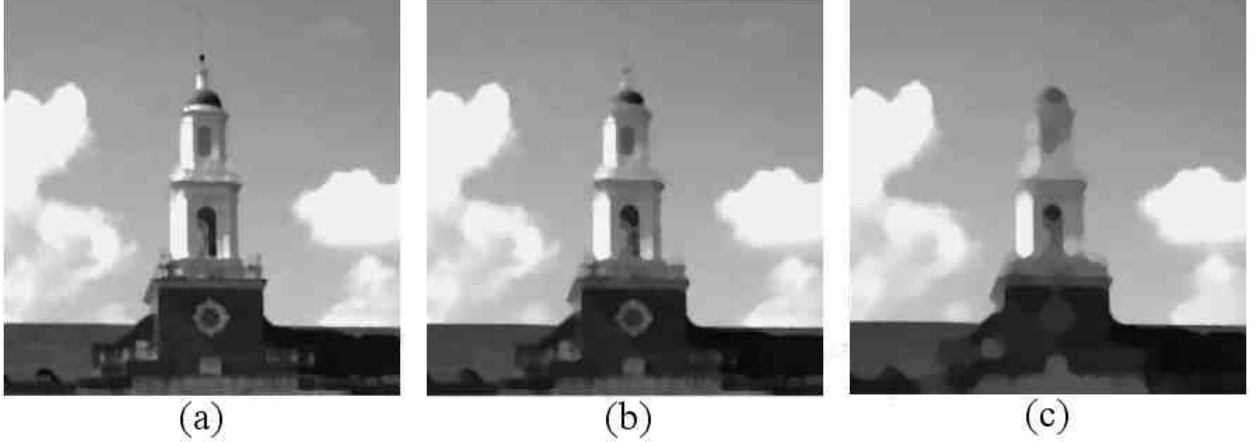

Figure 2 Morphological LOMO filter with circular structuring elements of radius (a) 1, (b) 2, and (c) 4 pixels.

The area morphology algorithms have the advantage (over traditional morphological filters) of maintaining the target boundaries after filtering at coarse scale. The disadvantage of the area morphological filters is the computational cost. Therefore, we have designed a pyramidal (multi-resolution) implementation of the area morphological operators that reduces the computational cost by three orders of magnitude (Acton and Mukherjee, 2000). The work in area morphology has also led to novel methods for image segmentation (Acton and Mukherjee, 2000; Mukherjee et al., 2002).

The nonlinear filters were used in conjunction with a correlation-based tracker on 17 sequences of 91 frames each. The tracking performance for each filter (and the case of no filtering) was recorded in terms of "percentage tracked." For a target of width 2r, the percentage tracked is computed by finding the number of frames in which the computed target center is within r of the actual target center. Compared to the performance on the unfiltered imagery, the morphological residue increased performance by 2% and anisotropic diffusion increased performance by 4%. Both the LOMO filter and the morphological residue increased performance significantly, by over 10%. The early experiments show that the traditional measures of enhancement quality (mean squared error, visual appearance, etc.) do not correlate with tracker performance. For example, the area morphological filters yielded the lowest edge localization error and the lowest mean squared error in intensity, but also provided the lowest performance improvement in tracking.

Speckle Reducing Anisotropic Diffusion (SRAD)

We developed a novel anisotropic diffusion filtering method, called speckle reducing anisotropic diffusion (SRAD), for reducing speckle noise from ultrasonic and radar imagery (Yu and Acton, 2002). The diffusion update mechanism for pixel location (*i,j*) in SRAD is as follows:

$$I_{i,j}^{t+\Delta t} = I_{i,j}^t + \frac{\Delta t}{|\boldsymbol{h}_s|} div(c(C_{i,j}^t)\nabla I_{i,j}^t), \tag{2}$$

where $c(\ldots)$ is a decreasing function as in traditional anisotropic diffusion (Perona and Malik, 1990), and $C_{i,j}^t$ is called the instantaneous coefficient of variation and is defined as:

$$C_{i,j}^t = \frac{\frac{1}{2}|\nabla I_{i,j}|^2 - \frac{1}{16}(\nabla^2 I_{i,j})^2}{[I_{i,j} + \frac{1}{4}\nabla^2 I_{i,j}]^2}. \tag{3}$$

We present two example results of speckle reduction on radar imagery in Figures 3 and 4. Recently we have extended SRAD from two dimensional processing to three dimensional processing, which yields better smoothing and edge preserving performance (Yu and Acton, 2004b).
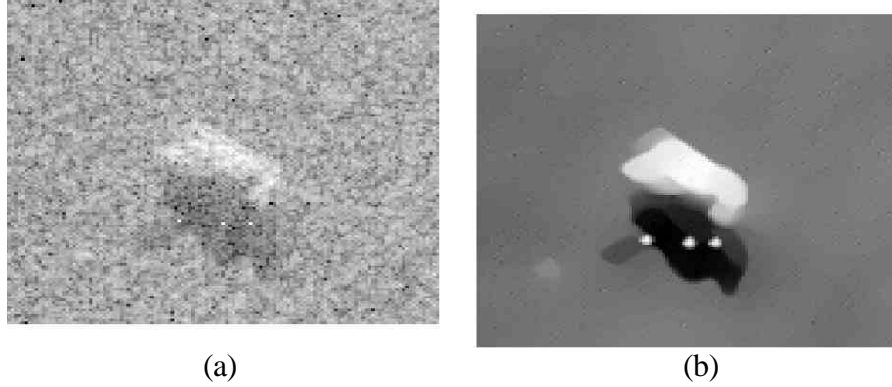

(a) (b)

Figure 3 (a) Radar image of T72 tank. (b) Result of SRAD.
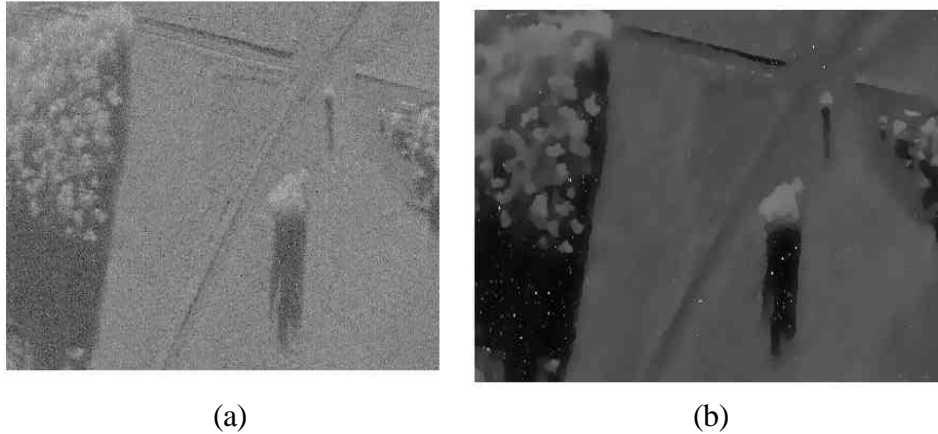

(a) (b)

Figure 4 (a) Radar image of a battlefield. (b) Result of SRAD.

We have also utilized instantaneous coefficient of variation in the context of edge detection (Yu and Acton, 2004a) and object delineation from speckled imagery. In a traditional parametric active contour (Kass *et al*., 1987) based object delineation approach, the typical external energy for the active contour is a function of the Gaussian smoothed image gradient magnitude. The Gaussian filtering is intended to remove noise and small features from the image, while the gradient magnitude is used to detect edges. For SAR imagery, Gaussian filtering and gradient edge detection are not suitable due to the presence of signal-dependent speckle noise. As already mentioned SRAD smoothes the imagery and enhances edges by allowing isotropic diffusion on an intra-region basis and inhibiting diffusion across edges, with the help of the *instantaneous coefficient of variation* (ICOV*)* edge detector. We propose that the external energy used for guiding the contour toward the edge of the target to be defined as

$$E_{ext}(x,y) = -\frac{\left| (1/2)|\nabla \tilde{I}_s|^2 - (1/16)(\nabla^2 \tilde{I}_s)^2 \right|}{\left[I + (1/4)\nabla^2 \tilde{I}_s \right]^2}, \tag{4}$$

where $\tilde{I}_s(x,y)$ is the SRAD filtered image, ∇^2 is the Laplacian operator, ∇ is the gradient operator and $|\ |$ denotes the magnitude. (4) is the additive inverse of the ICOV that allows for balanced and well localized edge strength measurements in bright regions as well as in dark regions. For radar and ultrasonic imagery, the ICOV external force provides a noise resilient method for image segmentation.

Signal-to-clutter Ratio

Methods have been developed for quantification of the tracking difficulty for video sequences by the average signal-to-clutter-ratio (SCR) and the average registration error. Clutter is measured by computing the similarity of the target signature with objects in the current image. Let T be the template of a target and Q the subimage of the target within the current image. Ω defines the neighborhood around the target: $\Omega = \{(k,l) : \sqrt{(k-x_0)^2 + (l-y_0)^2} \le 2R\}$, where R is the average radius of the target. The SCR is defined by

$$SCR = \frac{d(T,Q)}{\sum_{k,l \in \Omega} w_{k,l} d(T, P_{k,l}) / \sum_{k,l \in \Omega} w_{k,l}} \tag{5}$$

where $P_{k,l}$ is a subimage centered at (*k*,*l*), $d(T, P_{k,l})$ is a dissimilarity measure between the template T and subimage $P_{k,l}$, and $w_{k,l}$ is a weighting that depends on the distance of clutter from the target center. SCR plays a major role in measuring success or failure of a detection/tracking algorithm with respect to the quality of a video.

Inclusion Filters

We developed a morphological connected filter that either fills or retains the holes of the connected sets depending on application-specific criteria that are increasing in the set theoretic sense. We refer to this class of connected operators as inclusion filter, which is shown to be increasing, idempotent and self-dual (gray level inversion invariance) (Ray and Acton, 2004a). We demonstrate perfect self-duality for 8-adjacency on a discrete Cartesian grid. Inclusion filters are defined first for binary-valued images, and then the definition is extended to grayscale imagery via threshold decomposition principle. Theoretical connection between inclusion filters and other classes of connected operators, such as levelings, has also been explored (Ray and Acton, 2004a).

| (a) | (b) | (c) | (d) |

Figure 5 (a) A bird image. The user has mouse-clicked inside the head and neck of the bird (5 black dots). (b) After inclusion filtering the image with the markers (5 black dots). (c) edges of (a). (d) edges of (b).

Inclusion filters essentially smoothes an image without distorting the edges. Several important applications of inclusion filters are demonstrated – automatic segmentation of the magnetic resonance imagery, user interactive shape delineation, registration of video sequences, and detection and tracking of targets. The numerical performance measures on 100 tracking experiments show that the use of inclusion filter improves the total number of frames successfully tracked by five times and provides a threefold reduction in the overall position error (Ray and Acton, 2004a). Figure 5 shows an interactive image smoothing example.

Color Connected Operators

Connected filters have been used to denoise grayscale images without blurring feature boundaries, but these methods have not been extended to color/multispectral imagery. The standard approach to any color image processing is to apply filters to the red, green, and blue bands separately. As the three bands are not completely uncorrelated, the correlation often causes the introduction of new colors into the smoothed image due to artifacts. Incorrect coloring could lead to errors in later processing, e.g., classification, target identification and tracking.
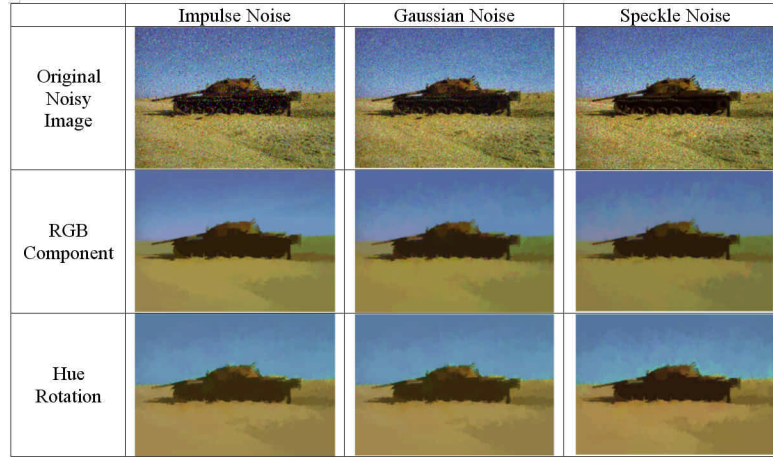
Figure 6 Examples of noisy and denoised tank images using area-open close filter.

We have developed a method of applying connected filters to color images using rotation in the hue band of the hue-saturation-value (HSV) color space (Weber and Acton, 2004). Because the hue band is circular (*i.e*., the maximum and minimum intensities values are similar shades of red), connected filters do not correctly join connected components in the hue band. This inaccuracy is particularly evident in images with a high amount of red. However, by rotating the hue band so this discontinuity occurs at an infrequent shade within the image (a "flat spot" on the hue histogram), this error is minimized. Our method is particularly effective in smoothing impulse noise in color and multispectral imagery. Figure 6 shows the application of the color connected operator to a tank image. The result with hue band rotation yields a more natural effect and does not bleed with the green as is the case in the middle row of the images that are produced by ordinary connected filtering on R-G-B bands. This filtering process could improve image classification where color information is utilized.

Video Stabilization in Moving Field of View

We developed an automated algorithm to minimize "jitter"- unwanted video frame displacement and to register video frames in a moving field of view (Goobic *et al*., 2004). Jitter is severely detrimental to tracking, contributing to unpredictable target movement. A morphological technique identifies *M* motion regions and *B* background regions and a modified cross correlation technique is applied to determine the necessary translation to register misaligned frames. We can align frames in a moving field of view to provide for tracking targets over an extended range. The algorithm has been tested using 60 high clutter video sequences where approximately one-third of the frames are displaced from the majority of frames. The average root mean square error (RMSE) was less than 2 pixels in the 60 experiments. Furthermore, we were able to track 11 targets over a total of 13 sequences in which both the target and the camera were in motion.

Projection/Affine Object Model, Projective/Affine Active Contour and Tracking

In general adapting any sequential Monte Carlo (SMC) method for tracking object with free form contour faces two major difficulties – (i) computational bottleneck as a free form object boundary is typically encoded via a number of parameters; and (ii) lack of robustness when tracking is performed in cluttered environments. We developed an SMC method that overcomes both these difficulties by encoding an object boundary via projective/affine transformation parameters (Welser and Acton, 2004). Additionally the method is easily adapted to target sequences that exhibit enormous change of target size (scale change). The method is explained in the following section.

Let (x_i, y_i), $i=1{:}M$ represents a set of ordered (clockwise or anticlockwise) coordinates of points on a 2D contour representing a target boundary. Due to the relative object/camera movement affine transformed object appears on the next frame and can be modeled as (Mukherjee, 1999):

$$x_i' = \mathbf{r}_x \cos(\mathbf{q})x_i - \mathbf{r}_x \sin(\mathbf{q})y_i + d \cos(\mathbf{j}), \ y_i' = \mathbf{r}_y \sin(\mathbf{q})x_i + \mathbf{r}_y \cos(\mathbf{q})y_i + d \sin(\mathbf{j}), \ i = 1{:}M,$$

$$(6)$$

where $\mathbf{q}$ represents rotation, $?_x$ and $?_x$ respectively are the x- and y-direction scaling, d is the magnitude of displacement and $\mathbf{j}$ is angle specifying the direction of displacement. Note that in this model the current object state is specified by the initial object position: (x_i, y_i), $i=1{:}M$, and five scalar parameters. Projective transformation is a more general one where parallel lines in the scene may no longer remain parallel after being projected on the camera plane. The transformed object position $(x_i', y_i'), i = 1{:}M$ and original object position $(x_i, y_i), i = 1{:}M$ are related in projective transformation as (Mukherjee, 1999):

$$x_i' = \frac{ax_i + by_i + c}{gx_i + hy_i + 1}, \qquad y_i' = \frac{dx_i + ey_i + f}{gx_i + hy_i + 1}, \qquad i = 1{:}M. \tag{7}$$

Note that in this case the object position is obtained by the initial target contour: (x_i, y_i), $i=1{:}M$, and eight scalar parameters a, b, c, d, e, f, g, and h. Thus our SMC method needs to generate only 5 (in the affine case) or 8 (in the projective case) parameters by random sampling and achieves the purpose.

Figure 7 provides a tracking result on military target sequences that involves partial target occlusions. The tracking result is seen to be encouraging here. The technique is also particularly useful in target sequences that undergo change of target scales – such as a "closure sequence" as shown in Figure 8 (Welser and Acton, 2004).
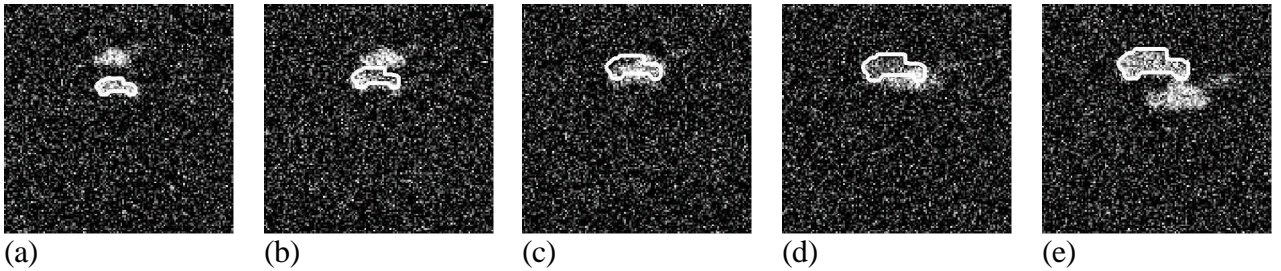

(a)　　　　　(b)　　　　　(c)　　　　　(d)　　　　　(e)

Figure 7 Occlusion sequence and tracking.

Figure 8 Successful tracking within a real closure sequence with the projection object model.

A similar and related active contour technique has also been developed under the same projective/affine transformation framework. Instead of letting the active contour evolve freely we propose to constrain the evolution to a family of affine transformation via minimization of the following energy functional:

$$E_{aff} = \int |\nabla I(x'(s), y'(s))| ds + \textbf{1} \sum_{A_{ij}} \frac{\partial |A|^2}{\partial A_{ij}} ; \ A = \begin{bmatrix} a & b \\ d & e \end{bmatrix} \tag{8}$$

The leftmost term in the energy functional is the integral of the image gradient along the affine curve, $(x(s),y(s))$, $s \in [0,1]$. Because large changes in the determinant of the affine matrix A significantly distort the contour, we include the rightmost term of (8) to ensure smoothness of the affine evolution. We update each affine parameter $\{a,b,c,d,e,f\}$ according to update equations that minimize this energy functional to smoothly evolve a curve that lies on high image gradient (on target edges). Updates for the snake positions are derived using variational calculus. The affine snake is a useful tool for tracking rigid targets through clutter and noise.

Segmentation and Tracking via Image Level Set Analysis

In object detection we often seek to minimize an energy functional which typically is a function involving object shape, image gradient magnitude along the object boundary and homogeneity inside the object. Traditional segmentation tools such as geometric active contours or template matching methods are computationally expensive in such cases. We proposed an expedient solution for seeking minima of the energy functional via image level set analysis (Mukherjee *et al*., 2004). An image level set is defined as a binary image obtained by thresholding the gray scale image at certain threshold.

The capture of the target boundary is considered as an evolution of a closed curve that maximizes image gradient along the curve enclosing a homogeneous region. An energy functional dependent upon the gradient magnitude along the target boundary, the region homogeneity within the target boundary and the spatial overlap of the detected targets is

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minimized using a variational approach. For tracking between frames, this energy functional is modified considering the spatial and shape consistency of a target as it moves in the video sequence. The integrated energy functional complements shape-based segmentation with a spatial consistency based tracking technique. We demonstrate that an acceptable, expedient solution of the energy functional is possible through a search of the image level lines – boundaries of connected components within the level sets obtained by threshold decomposition. The level set analysis can also capture multiple targets in a single frame rather than iteratively computing a single active contour for each individual target.

Lie Groups and Active Contours

A novel technique has been developed to constrain contour evolution within a Lie group of plane transformations (Mansouri *et al*., 2004). Such an evolution technique is shown to be quite robust in delineating object boundary in presence of severe clutter. An example application of the technique is shown in Figure 9, where a target is being tracked with a contour that is constrained to undergo planar affine transformations. This technique has the potential to play significant role in military target tracking application. In Table 1 we report constrained active tracking results on three different target types.
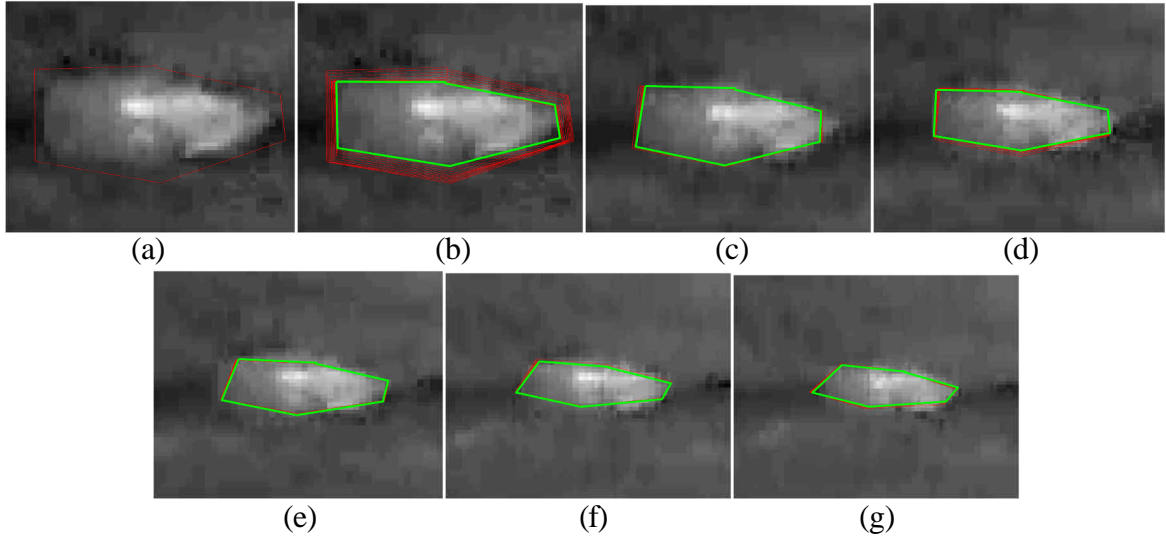

Figure 9 Results of tracking tank in clutter by affine object model and proposed MCMC algorithm. (a) initial contour in frame 0, (b) frame 0, (c) frame 5, (d) frame 10, (e) frame 15, (f) frame 20, and (g) frame 25.

Sequence		Frame Number						
		1st	3rd	5th	10th	15th	20th	25th
Blood Cell	Affine	+7.31	-0.78	-1.89	-1.29	-3.43	-2.1	-1.51
	Unconstrained	-10.22	+1.32	-8.02	-7.33	-4.75	-1.99	-1.7
Table Tennis	Affine	+0.43	–	+1.28	+1.93	+0.21	+0.94	+1.18
	Unconstrained	-2.32	–	-2.85	-1.50	-4.39	-2.83	-1.08
Tank	Affine	-2.31	–	-6.74	-5.12	-3.83	-7.37	-12.31
	Unconstrained	+5.37	–	+3.2	+4.2	+1.7	+1.24	-0.46

Motion Gradient Vector Flow (MGVF)

An active contour is a 2D curve that can move on an image domain and capture desired image features. When the desired image feature to be captured is an edge, the image gradient force acts as the governing force for the contour that actually moves the contour towards to the edge. However, the image gradient force has been discovered to be insufficient because it can only attract nearby contours, but not the distant ones. Thus, another active contour force model called *gradient vector flow* (GVF) has been proposed (Xu and Prince, 1998). GVF diffuses the image gradient magnitude force away from the edge and so is able to attract the contour from a distance. Although suitable for target delineation from a single frame, GVF has no special capability for object tracking accommodating the object motion. We propose motion gradient vector flow (MGVF) imbedding the target motion direction into the force field. The force field is realized by minimizing an energy functional as follows (Ray and Acton, 2004b):

$$E_{\text{MGVF}}(w) = \frac{1}{2} \iint [\boldsymbol{m} H_e (\nabla w.(v^x, v^y)) \,|\, \nabla w \,|^2 + f\,(w - f)^2] dx dy, \qquad (9)$$

where f is the magnitude of image gradient, (v^x, v^y) is the object motion direction (known *a priori* or estimated), H_e is a regularized Heaviside function, and $\boldsymbol{m}$ is a non-negative weighting parameter controlling diffusion.

After minimization of the energy functional, we obtain the MGVF field, ∇w, which guides the active contour towards the target even if initial contour, lagging behind the moving target, has minimal overlap. So, this specialized model can be applied successfully to delineating moving targets with active contours. A convergent implementation on 8-neighborhood system is as follows:

$$w_{i,j}^{t+1} = w_{i,j}^t + \frac{\boldsymbol{m}}{l} \sum_{l=-1}^{1} \sum_{m=-1}^{1} H_e ((lv^y + mv^x)(w_{i+l,j+m}^t - w_{i,j}^t))(w_{i+l,j+m}^t - w_{i,j}^t) - \frac{1}{l} f_{i,j}(w_{i,j}^t - f_{i,j}),$$

$$(10)$$

provided:

(i) the edge-map f is normalized:

$$0 < d \leq f_{i,j} \leq 1, \forall i, j,$$

and

(ii) we select the multiplicative inverse of the time-step as:

$$l \geq 1 + 8m.$$

Table 2 Average position error (measured in microns) of GVF and MGVF tracking methods for four frame rates.

	Original frame rate (30 fps)	Half frame rate (15 fps)	One-third frame rate (10 fps)	One-fourth frame rate (7.5 fps)
Mean GVF tracking RMSE	2.5	2.7	4.3	6.0
Mean MGVF tracking RMSE	1.6	1.5	1.8	3.9

Table 2 provides a comparison of MGVF and GVF tracking method for 100 target sequences obtained from microscopic videos. The comparison shows that MGVF outperforms the GVF tracker even when frame rate (temporal resolution for a video) is less. Thus throwing away some frames in MGVF tracking method will yield gain in computation without sacrificing tracking quality.

Gradient Inverse Coefficient of Variation (GICOV)

Object detection in clutter is always a challenging problem in computer vision and image processing. We developed a likelihood statistic for object detection that is the ratio of mean and standard deviation of the directional gradients computed over the length of a contour delineating the object. We call this new statistic as gradient inverse coefficient of variation (GICOV). Analysis of GICOV has led to the fact that it follows student t distributions (Dong *et al*., 2004). Experimental results using 327 targets were compared to those of human experts and currently used methods. The GICOV method achieves 78.6 percent detection accuracy with 13.1 percent false alarm rate (Dong *et al*., 2004). Currently we are making efforts towards utilizing the same statistics in other cluttered environments (FLIR imagery) to detect military targets.

Let $(X(s), Y(s))$ represent a 2D smooth contour parameterized through $s \in [0, 1]$. If $I(x, y)$ denotes an image then the mean of the image gradient over the entire contour computed in

the outward normal direction is given by

$$M(X,Y) = \frac{1}{L}\int_0^1 \nabla I(X(s),Y(s)) \cdot \mathbf{n}(X(s),Y(s))\,ds,$$

where $\mathbf{n}(X(s), Y(s))$ is the unit outward normal to the contour at $(X(s), Y(s))$ and L is the length

of the contour given by $L = \int_0^1 \sqrt{X_s^2 + Y_s^2}\,ds$. (11)

Likewise, the variance of the image gradient over the entire contour computed in the outward normal direction $\mathbf{n}$ is given by

$$S^2(X,Y) = \frac{1}{L}\int_0^1 [\nabla I(X(s),Y(s)) \cdot \mathbf{n}(X(s),Y(s))]^2\,ds - M^2(X,Y).$$ (12)

We define the gradient inverse coefficient of variation (GICOV) as

$$V(X,Y) = \frac{M(X,Y)}{S(X,Y)\big/\sqrt{L}}.$$ (13)

where $\sqrt{L}$ works as a normalization constant. Thus, in order to seek an object boundary in a cluttered environment we want to locate a contour (X^*, Y^*) such that

$$(X^*,Y^*) = \arg\max_{X,Y} V^2(X,Y).$$ (14)

For tracking in clutter, the GICOV measure is an effective detection statistic. We plan to continue research on this important topic.

C. PUBLICATIONS

Papers published/accepted in peer reviewed journals

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Papers submitted/in review at peer reviewed journals

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Papers presented at meetings but not published
None.

D. PARTICIPATING PERSONNEL AND DEGREES AWARDED

Name	Degree Awarded
<u>Name</u>	<u>Degree Awarded</u>
1. Robert Janiczek	B.S. May 2003, M.S. expected August 2004
2. Adam Goobic	B.S. May 2002, M.S. May 2003
3. Michael Welser	B.S. May 2002, M.S. May 2003
4. Sridhar Reddy Avula	M.S. December 2003
5. Kate Weber	M.S. May 2003
6. Nilanjan Ray	Ph.D. May 2003
7. Yongjian Yu	Ph.D. May 2003
8. Sean Jellish	M.S. August 2004
9. John Pickard	M.S. expected May 2005
10. Bing Li	M.S. expected May 2005
11. Gang Dong	Ph.D. expected August 2005

E. REPORT OF INVENTIONS

No patents or reportable inventions.

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